

Determining How Functional Characteristics of a Dedicated Casualty Evacuation Aircraft Affect Patient Movement and Outcomes

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Abstract

Advances in autonomous aircraft technology are spurring research into different roles these aircraft could fill. The Office of Naval Research (ONR) is pursuing an Innovative Naval Prototype of an autonomous cargo aircraft in response to a United States Marine Corps Universal Needs Statement. Since the use of such a vehicle to evacuate casualties after delivering supplies is an obvious extension, ONR initiated research into how the functional characteristics of an aircraft such as speed, range, capacity, and number available affect how the aircraft performs as a patient movement platform. To evaluate aircraft functional characteristics we execute experiments with a patient movement simulation that explicitly models treatment, evacuation, and mortality as a patient flows from the point of injury through definitive care. The experiments provide data from which to develop a response surface model of estimated patient mortality as a function of the casualty evacuation system characteristics. This response surface will be useful for comparing competing systems when currently unknown constraints such as total cost of ownership, volume, area and weight are applied.

Key Words

Simulation, casualty evacuation, unmanned aircraft, response surface

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1. Introduction

As technology driving autonomous and remotely operated machines matures, these machines will support a broader spectrum of more complex missions. The Office of Naval Research (ONR) develops technology to support continually evolving Navy and Marine Corps Warfighting concepts. Recent trends in Marine Corps and joint services strategic planning focus on supporting operations from a sea base [1]. The sea basing concept reduces or eliminates the logistics train traditionally deployed ashore to support combat forces. Reducing the population at risk on shore naturally reduces the likely number of casualties. Eliminating the tether to a logistics train increases the mobility and independence of fighting forces. A smaller logistical footprint ashore also increases the burden on aircraft or some other novel means for delivering time critical supplies to the battlefield and evacuating casualties over potentially long distances. This delivery and evacuation mechanism is a critical capability for the sea basing concept; our analysis focuses on casualty evacuation for Enhanced Company Operations (ECO) supported from the sea.

ECO is an extension of the Distributed Operations (DO) concept developed by the Marine Corps Warfighting Laboratory (MCWL) between 2004 and 2006 [2]. The DO concept develops squads and platoons as more capable independent units. ECO extends this concept to the company level and MCWL is currently conducting tests to ensure feasibility and performance. A scheduled 2010 test of ECO supported from the sea will stress all communications and logistics functions, including MEDEVAC, with significant distances involved [3].

Several concepts using autonomous systems to evacuate casualties already exist. The Fisher Institute for Air and Space Strategic Studies in Israel is developing the MedUAV concept vehicle for medical resupply and casualty evacuation [4]. MCWL is testing an autonomous Boeing Little Bird to fly casualties from the Point of Injury (POI) to an Ambulance Exchange Point (AXP) or to forward surgical facilities [5]. The Defense Advanced Research Projects Agency's (DARPA) Nightingale feasibility study examined technologies required for implementing autonomous vehicles for casualty evacuation and found the concept viable; the Pentagon began issuing Small Business Innovation Research contracts related to a casualty evacuation Unpiloted Aircraft System (UAS) in 2007 [6]. Most UAS concepts for evacuating casualties include some means of delivering care en route. Gilbert et al [7] provide an excellent catalog of past and current research efforts to develop remote and automated care providing systems expected to deliver more advanced care than a current first responder. Ample research is underway to develop technologies required to field an autonomous aircraft designed to move patients, but little research exists quantifying how such systems will impact patient movement and outcomes when fielded.

Our analysis seeks to determine how the characteristics of a dedicated Medical Evacuation (MEDEVAC) UAS impact patient movement and outcomes. We include operational environment, casualty burden, aircraft speed, aircraft capacity, number of available aircraft, aircraft range, and crash frequency of evacuation missions as variables in a simulation experiment. Featherstone conducts a comparable analysis with similar variables [8]. While Featherstone's analysis contains greater detail for enemy action and aircraft flight operations, our effort includes more detailed estimates of how the time required to reach a medical facility affects patient outcomes. Our primary performance metric is the percentage of critical casualties who die during evacuation. Both analyses examine movement from the POI to a Forward Resuscitative Surgery System (FRSS), but we also evaluate UAS characteristics when forward surgery is unavailable and casualties move from the POI to a sea based facility up to 370 km away. Featherstone focuses on UAS performance, but recommends an evaluation of MV-22 performance [8]. Our analysis is comparative; the performance of each UAS system is measured against MV-22 performance as a baseline.

2. Key Assumptions and Modeling Limitations

The list of below is not exhaustive but highlights items that most influence the context of our results.

1. All evacuation is via aircraft, no ground evacuation is available.
2. Simultaneous casualties from the same platoon will evacuate from a single location.
3. Patients requiring a litter or with life threatening injuries evacuate with the highest priority and request dedicated MEDEVAC aircraft.
4. Ambulatory patients may board a dedicated MEDEVAC aircraft if space is available, but will request only Lifts Of Opportunity (LOO) for evacuation.
5. LOO are aircraft not dedicated to MEDEVAC that can opportunistically pick up casualties as they perform other missions. We model these by randomly selecting a delay from a distribution that represents the amount of time until the LOO arrives at the casualty's location.
6. Patients requiring a litter or with life threatening injuries evacuate to a forward surgical facility if available, and receive more accurate triage there.
7. Patients who die at or near the point of injury evacuate with high priority, but with lower priority than any surviving patient requiring a litter or with life threatening injuries. Small units in ECO cannot handle deceased persons so removing them from the battlefield is important.
8. A UAS fielded for MEDEVAC will provide adequate en route care through some means (automated, remote, or on board corpsman) equal to current levels of en route care
9. Patient outcomes are not affected by lack of en route care providing capability of LOO aircraft (we discuss this assumption further in section 8).
10. The FRSS is always collocated with a Forward Arming and Refueling Point (FARP) and a Shock Trauma Platoon (STP).

11. If available, dedicated MEDEVAC aircraft operate from the FARP.
12. UAS have a five minute faster response time than MV-22 because less human activity is required to launch.
13. Aircraft travel linear distances between their base location and the casualty location—a distance of 30 km means a 30 km flight distance.

3. Operational Phases

Our analysis evaluates casualty evacuation in two phases of ECO, an Initial Assault phase and a Security Operations phase. Subject Matter Experts from the Marine Corps Warfighting Laboratory (MCWL) provide details of the operational phases. In the Initial Assault, units maneuver to their objectives, take those objectives, and then remain in place. We observe a 96 hour period of operation. Figure 1 illustrates the geometry of tactical objectives and important locations for combat operations.

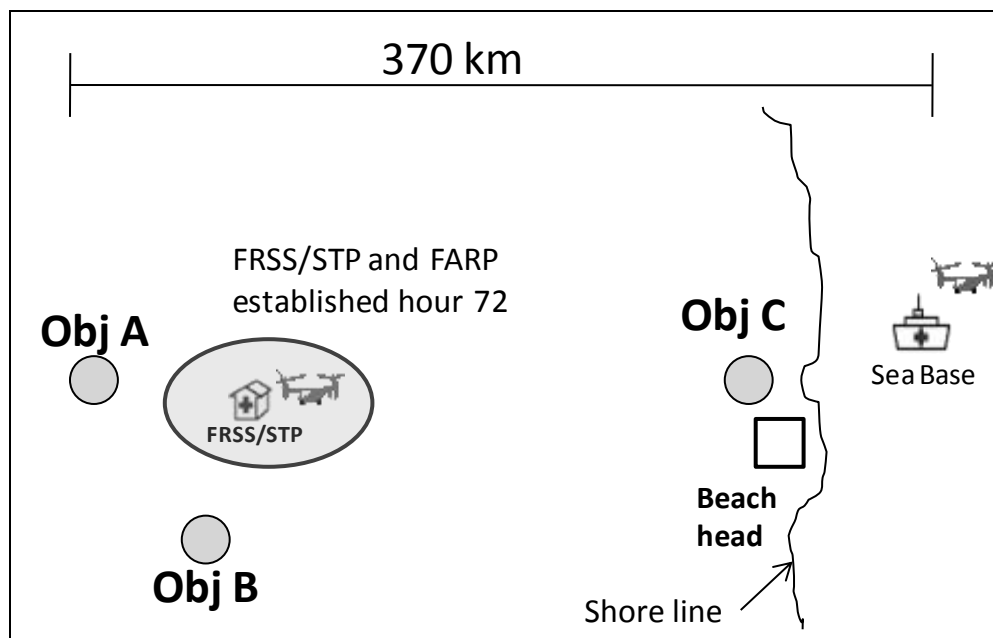


Figure 1 Initial Assault geometry

At hour zero, one company assaults objective A, and a second company lands on the beachhead. The company on the beachhead maneuvers to objective C, assaults it, and waits for relief. When the third company relieves objective C, the second company maneuvers inland and takes objective B. All of these assaults occur before the FARP and FRSS are operational. In the Initial Assault, most critically wounded patients must travel back to the sea base to receive their first surgery. Each company is dispersed in an Area of Operations (AO) with a 5 km radius as it maneuvers and fights. Casualties arrive in concentrated periods of approximately one hour during the assaults with occasional Multiple Casualty Events (MCE) where several injuries occur simultaneously. Patients with disease and non battle injuries arrive sporadically throughout the operation.

The Security Operations phase occurs after units take their objectives in an assault. Three rifle companies conduct patrols and man checkpoints in three distinct AOs each with a radius of 10 km. Casualties arrive sporadically throughout a 96 hour period of observation, and several isolated Multiple Casualty Events (MCE) result from attacks such as ambushes or roadside bombs. Squads and platoons are dispersed and operate independently. Figure 2 illustrates a hypothetical battlespace geometry. The FRSS/STP is always available.

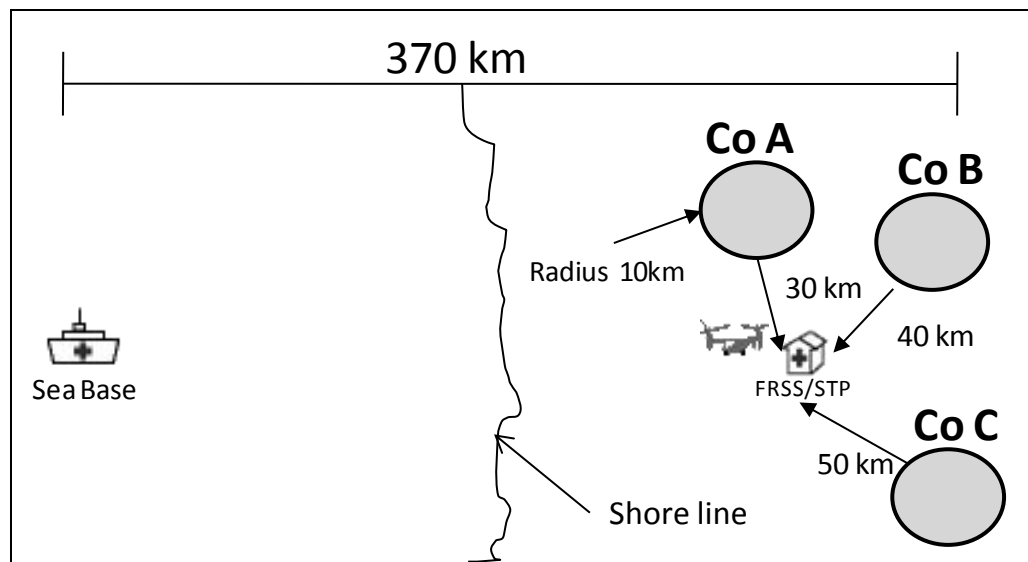


Figure 2 Security Operations geometry.

4. Discrete Event Simulation

ONR partnered with the Naval Health Research Center (NHRC) to utilize the Tactical Medical Logistics (TML+) planning tool. TML+ is a discrete event simulation that models the treatment, evacuation and outcome of patients as they move from the Point of Injury (POI) to definitive care. The model includes treatment profiles for over 300 Patient Condition (PC) codes at Navy expeditionary medical capabilities. TML+ models patients, care providers, equipment, supplies, treatment tasks, transportation assets, patient movement, vehicle crashes, and patient mortality.

We use independent arrival processes to represent different POI. Each company Area of Operations (AO) has three independent arrival processes to represent three platoons. When a casualty or group of casualties arrives in the simulation, the distance from the aircraft to the POI is computed by adding a Triangular random variable to the shortest possible distance from the aircraft location to the company AO. The random component of the distance models the effect of casualties arriving in different locations within the circular AO. Aircraft can make multiple stops within a single AO but do not pick up casualties in more than one AO per trip.

Figure 3 illustrates how TML+ models treatment within each medical facility. A facility is composed of one or more functional areas, such as the pre-operation and operating rooms at a surgical facility. Each patient completes a series of tasks in each functional area, and each task requires personnel and sometimes equipment. In each functional area, patients can either

Return to Duty (RTD) or Die of their Wounds (DOW). During treatment at the last functional area of a facility, each patient requests an evacuation asset. Patient routing, loading, and vehicle assignments are based on user defined patient movement rules, and PC priorities.

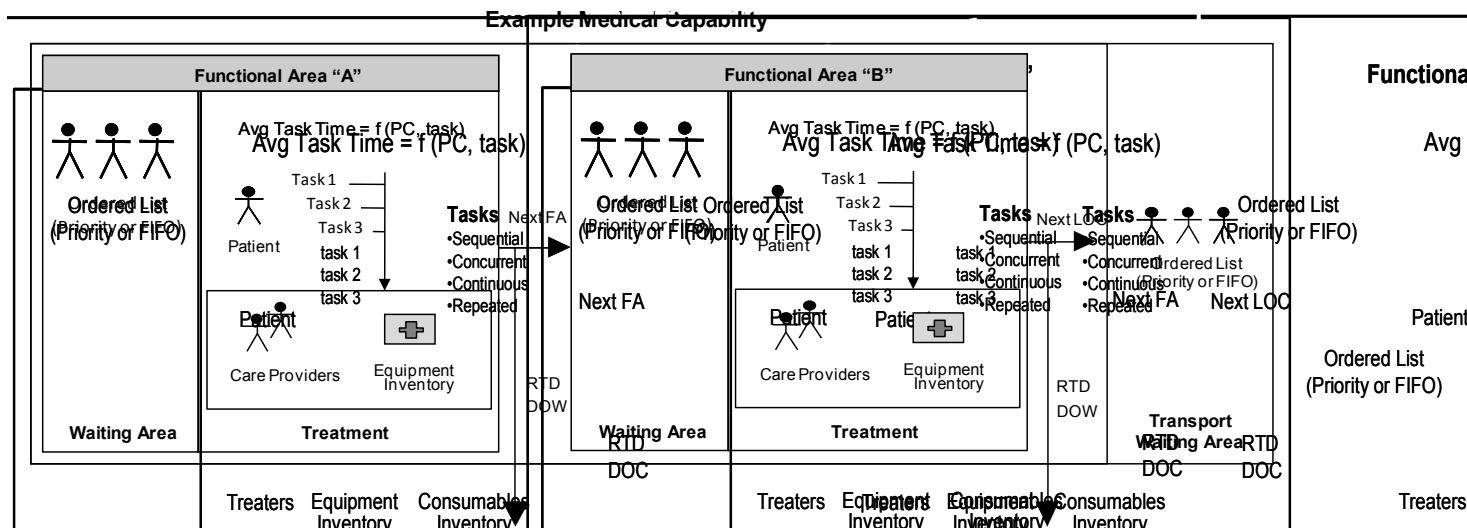


Figure 3 Casualty treatment modeling [8]

TML+ models transit times as a function of vehicle speed and distance and it uses simple delays to model other activities associated with casualty evacuation. A request for evacuation selects an available transport and initiates a pre-mission delay before the transport leaves its current location to retrieve a casualty. The pre-mission delay accounts for time associated with personnel transmitting and receiving the request, processing the request, alerting an aircraft, and aircraft engine start and warm up. We set this time at 15 minutes based on inputs from input from the Marine Corps Warfighting Laboratory (MCWL). TML+ computes flight time solely from speed and distance. An additional five minutes added to the flight time accounts for takeoff, acceleration, deceleration and landing. Aerospace Engineers at the Naval Air Systems Command (NAVAIR) Advanced Aircraft Design division conducted computer simulations that modeled actual flight maneuvers of various aircraft configurations to estimate this additional time. When an aircraft lands at the casualty's location, patients load by priorities based on injury severity. Loading and unloading time is two minutes for ambulatory patients and three minutes for litter patients. The casualty then proceeds to the next level of care, and unloads from the aircraft. When the last patient is unloaded the aircraft returns to its base location and is available for requests.

TML+ estimates patient mortality with a series of Weibull density functions representing a patient's remaining survival time given the current history of care that patient received [9]. Different coefficients reflect different histories of care. Table 1 lists the possible progressions of care a casualty could encounter. Weibull densities with different coefficients represent the distributions of survival times for patients of three different risk categories for each row in the table. Each patient condition is high, medium or low risk. These curves were originally developed by polling a panel of doctors with recent combat experience [10], but recent work by

Mitchell et al [11] demonstrates that portions of the panel results match reasonably well with empirical data from the Navy Marine Corps Combat Trauma Registry (CTR).

Table 1 Progression of care providing capability

No Treatment	1st Care	2nd Care	3rd Care	4th Care
Self-Buddy Aid	--	--	--	--
Self-Buddy Aid	First responder	--	--	--
Self-Buddy Aid	First responder	Shock Trauma Platoon	--	--
Self-Buddy Aid	First responder	Forward Surgery	--	--
Self-Buddy Aid	First responder	Shock Trauma Platoon	Forward Surgery	--
Self-Buddy Aid	First responder	Shock Trauma Platoon	Surgical Facility	--
Self-Buddy Aid	First responder	Shock Trauma Platoon	Forward Surgery	Surgical Facility

TML+ computes a patient's time of death by randomly selecting a survival time from the appropriate Weibull distribution. This computation occurs at the time of injury, and each time a patient begins treatment at increasingly capable medical facilities. Figure 4 below helps illustrate how these curves model mortality. When a patient arrives at a first responder, a random survival time from the Weibull distribution representing that patients level of risk and current history of care determine when the patient will die without further intervention. If it takes 30 minutes to arrive at a Shock Trauma platoon since beginning treatment at a first responder, the likelihood that a high risk patient will still be alive is about 0.7. If the patient begins treatment before his survival time has elapsed, a random selection from a flatter Weibull distribution computes a new survival time based on the patients updated history of care.

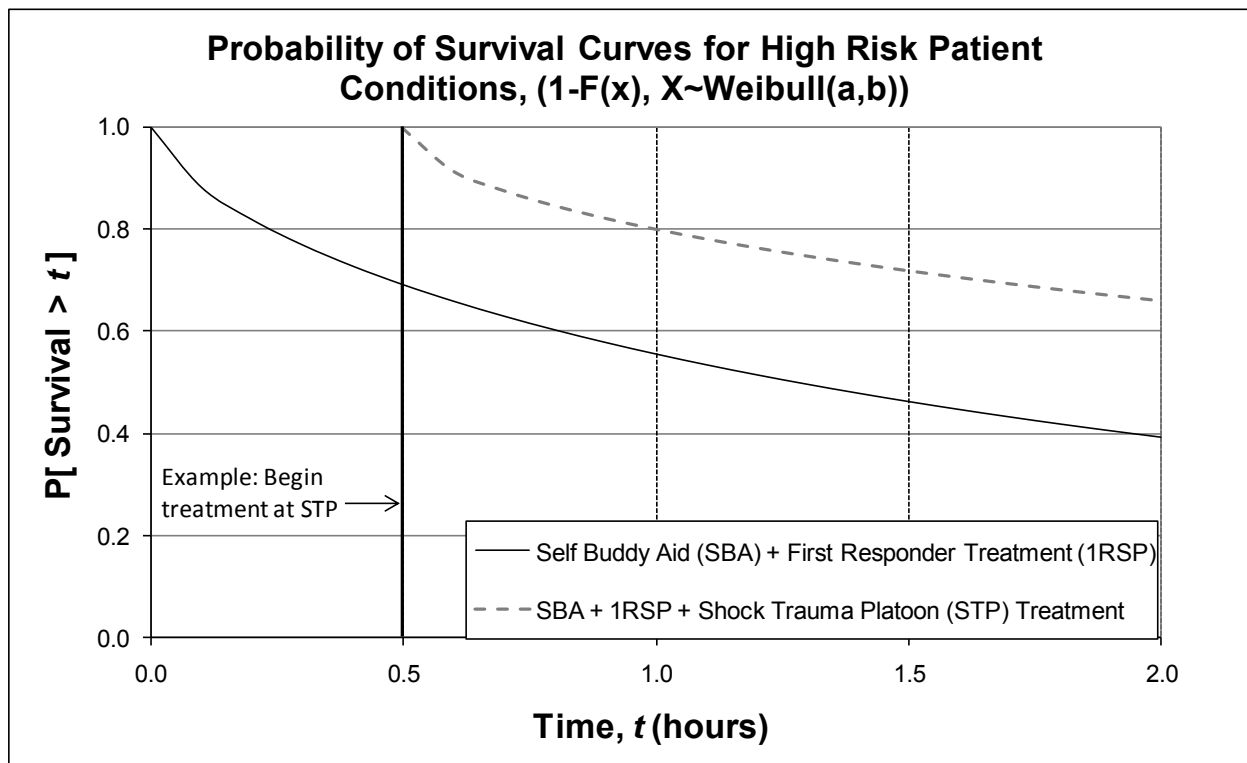


Figure 4 Progression of survival curves as level of treatment increases

5. Experiment

Casualty evacuation occurs under different operational conditions, and concepts of aircraft deployment alter how the characteristics of the aircraft system influence patient outcomes. We consider two phases of ECO supported from a sea base: Initial Assault and Security Operations. We evaluate three concepts of aircraft deployment: a short range aircraft moving patients from the point of injury to forward surgery or an Ambulance Exchange Point (AXP), a long range aircraft moving patients from the point of injury to any point as far as the sea base, and during the Initial Assault we consider a long range aircraft deployed the same way a short range aircraft would be.

Table 2. Aircraft concept and phase of operations

Phase of operation Aircraft range and employment concept	Initial Assault	Security Operations
Short Range (forward deployed for initial assault)	<ul style="list-style-type: none"> – Aircraft operate from the field, following combat units in trace – Aircraft move casualties from point of injury to ambulance exchange point 	<ul style="list-style-type: none"> – Aircraft operate from FARP – Aircraft move casualties from point of injury to forward surgery
Long Range	<ul style="list-style-type: none"> – Aircraft operate from the sea base – Aircraft move casualties all across the battlespace 	<ul style="list-style-type: none"> – Aircraft operate from FARP – Aircraft move casualties from point of injury to forward surgery
Long Range (forward deployed)	<ul style="list-style-type: none"> – Aircraft operate from the field, following combat units in trace – Aircraft move casualties all across the battlespace 	N/A

For each cell in Table 2, we perform a series of full factorial experiments of the following variables and levels to evaluate aircraft system characteristics. We used full factorial experiments because model run time was not a limiting factor we wanted to observe the response at each combination of the levels below. There are 192 runs of each UAS experiment for the tactical phases and aircraft concepts described in Table 2 for 960 UAS runs. Each run is replicated 40 times.

Table 3. UAS variables and experimental levels

Factor	Low ----- Levels -----> High			
Mean Casualty Burden (over 96 hours)	35		87	
Mission Failure (Crash) Rate	1/1000		1/500	
Number of Dedicated Aircraft	1	2	3	
Aircraft Speed (kmh ⁻¹)	150	220	315	555
Aircraft Capacity (litters)	1	2	3	6

The mean casualty burden in the Table 3 is the total expected number of patients over a 96 hour period in a non-stationary Poisson arrival process. The total number of casualties and injury distributions are the same for both operational phases, but the arrival processes are very

different as described in section 3. The low level of casualty burden results from the Ground Forces Casualty Forecasting System (FORECAS) [12]. The high level of casualty burden is simply a multiple of the low level. The multiple matches Forward Resuscitative Surgery System (FRSS) throughput during the heaviest 30 hour period of the simulation to FRSS throughput during a 30 hour period of intense fighting at Fallujah in 2004 reported by CAPT HR Bohman (FRSS surgeon) [13].

Mission Failure Rate (MFR) is an estimate of the probability that an aircraft catastrophically fails during a mission—either due to pilot error, mechanical failure, or enemy action. The levels in the table are estimates provided the Naval Air Systems Command (NAVAIR). The low level is the approximate reported crash rate for all aircraft missions during portions of Operation Iraqi Freedom (OIF) and Operation Enduring Freedom (OEF). The high rate is the approximate reported crash rate for UH-60 MEDEVAC missions.

The levels for speed indicate the points at which major design changes to the aircraft occur in terms of engine size, aircraft size, or type of aircraft, and were also provided by NAVAIR. We originally included a UAS speed of 425 kmh^{-1} , but earlier sensitivity analysis showed the response was very linear between 315 kmh^{-1} and 555 kmh^{-1} so we didn't include it in the final experiments. The number of aircraft number one to three. The Marine Corps Warfighting Laboratory indicated that four dedicated aircraft was probably the largest feasible number, and preliminary sensitivity runs showed very little change in the response from three aircraft to four so the final experiments set three aircraft as the highest level.

A set of baseline runs estimates the performance of current CASEVAC capability by evaluating the MV-22 Osprey in the CASEVAC role. The full factorial experiment on the factors and levels in Table 4 evaluates current capability in each operational phase for a total of 16 MV-22 runs, also replicated 40 times each. The full factorial experiment for the MV-22 provides a two control groups, one MV-22 and two MV-22, for each UAS system so that the control has have the same casualty rate and MFR as the UAS system.

Table 4. MV-22 Osprey variables and levels

Factor	Low -----	Levels -----> High
Mean Casualty Burden (over 96 hours)	35	87
Mission Failure (Crash) Rate	1/1000	1/500
Number of Dedicated Aircraft	1	2

Comparing each UAS system to the corresponding MV-22 baseline reduces the number of replications necessary to adequately estimate a measure of system performance and provides a frame of reference for system performance. TML+ synchronizes random number streams for Common Random Numbers (CRN). Yeng and Nelson demonstrate that applying CRN when comparing simulations of numerous systems to a single control system improves the sensitivity of multiple comparisons techniques [14]. We don't present the statistical tests for each system, but the improved sensitivity they describe manifests by significantly reducing the computational effort required to observe a stable estimate of the difference between a UAS system and the MV-22 control.

For replication j of each UAS configuration i , X_{ij} in equation (1) defines the percentage of patients who die during evacuation among patients at risk of death during evacuation. This percentage defines the performance of a particular system.

$$X_{ij} = 100 * \frac{\text{deaths during evacuation}}{\text{number at risk during evacuation}} \quad (1)$$

The same calculation gives system performance for replication j of an appropriate MV-22 system Y . The data of interest is the difference between each UAS system and the corresponding MV-22 control. We compare each UAS system to a single dedicated MV-22 and to two MV-22s, and denote these MV-22 systems by Y_1 and Y_2 respectively. All comparisons maintain equality of the operational phase, casualty burden and the MFR. So for each of the 960 UAS cases, we compute the average difference \bar{D}_{1i} in the performance of the UAS system i and 1 MV-22 in equation (2).

$$\bar{D}_{1i} = \frac{1}{40} \sum_{j=1}^{40} (X_{ij} - Y_{1j}), \quad (2)$$

\bar{D}_{2i} is computed similarly for two MV-22s. If $\bar{D}_{1i} = 5$, then the likelihood of death during evacuation with UAS system i is an average of 5% greater than with the single MV-22 baseline.

6. Influential Factors

Our analysis seeks to identify factors of an aircraft system that wield significant influence over patient mortality and to build response surface models of patient mortality as a function of the characteristics of the aircraft system. To determine the most significant aircraft system factors on patient mortality, we examine the highest and lowest levels of the variables described in section 0 to make two level experiments. Analysis of Variance on all replications of these two level experiments estimates effect sizes and relative influence on the response. To build response surface models we apply stepwise regression algorithms to the set of mean differences defined in equation (2) for each UAS system.

Operational phase, casualty burden and aircraft range drastically influence the nature and performance of the system, so we analyze each of these portions of the experiment separately. The data indicate speed is the most influential factor affecting patient mortality estimates from TML+, but the relative influence of speed changes with the distances involved. Figure 5 illustrates F statistics and associated p-values resulting from ANOVA on experiments with different aircraft ranges and heavy casualty burdens. The long range aircraft on the left side of Figure 5 moves casualties up to 370 km one way. The short range aircraft on the right side of Figure 5 moves casualties up to 140 km one way. Obviously the relative contribution of speed to variance is greatly reduced for the short range aircraft.

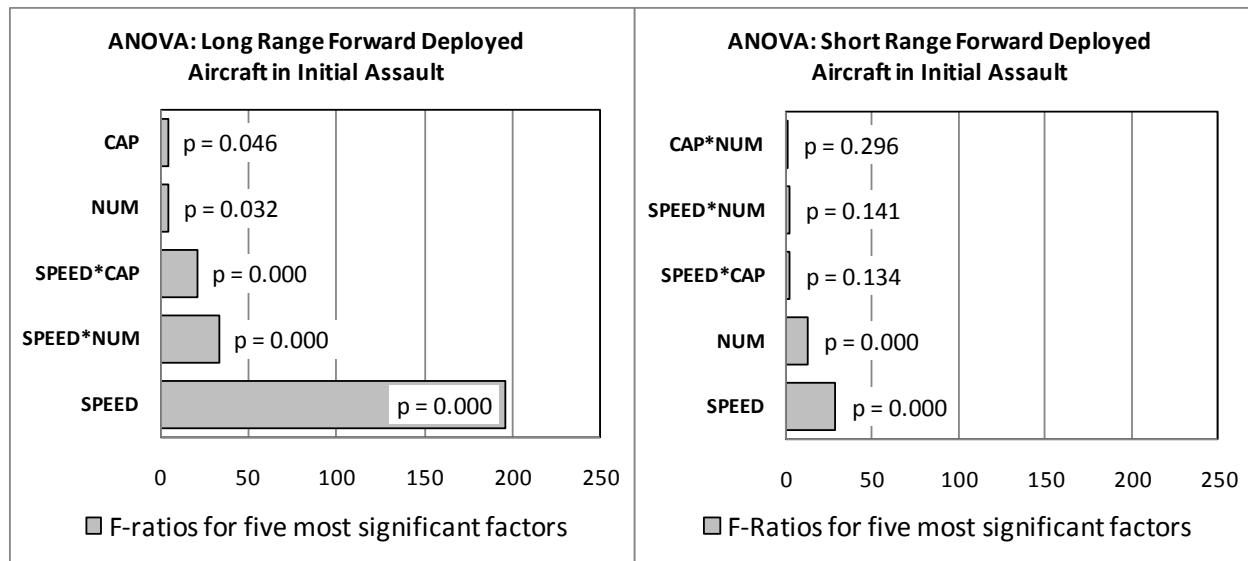


Figure 5. Difference in the influence of speed for different vehicle range.

Table 5 lists the effect sizes of all significant main effects in each operational phase, for each casualty burden, for each aircraft concept (short range, long range, long range forward deployed) when compared to a single MV-22. The effect size is simply the change in the average response (over all \bar{D}_{ii} in the two level experiments) from the low level to the high level of each main effect. For instance, the effect of speed at the base casualty rate, for a short range aircraft, in Security Operations is -5. This means that over all levels of the other factors, changing the aircraft speed from 148 kph to 555 kph reduces the mean percentage of mortality among those at risk by 5%.

Table 5. Size of significant effects (change in percentage deaths)

		Short Range	Long Range	Long Range (forward)
Security Operations		Effects Sizes	Effects Sizes	Effects Sizes
Base Casualty Rate	Speed	-5	-5	
	Capacity	-1.4	-1.4	
	Number	Not significant	Not significant	
	MFR	-2.6	-2.6	
Heavy Casualty Rate	Speed	-5.4	-5.4	
	Capacity	-1.1	-1.1	
	Number	-2	-2	
	MFR	-2.3	-2.3	
Initial Assault				
Base Casualty Rate	Speed	-3.7	-12.6	-9
	Capacity	-0.4	-1	-0.5
	Number	-4.7	Not significant	-0.9
	MFR	Not significant	Not significant	Not significant
Heavy Casualty Rate	Speed	-3.2	-12.2	-8.6
	Capacity	Not significant	Not significant	-1.3
	Number	-2.1	Not significant	-1.4
	MFR	Not significant	Not significant	Not significant

In the Initial Assault, speed for the long range aircraft is so important because there is no forward surgery available. In the Security Operations phase there is no difference in the effect size of speed between long range and short range aircraft. Mission Failure Rate doesn't appear to be significant in the Initial Assault but this is probably just a modeling artifact. Since there is no intermediate stop at forward surgery, there are simply fewer trips during the observation period, and consequently fewer crashes in the Initial Assault.

7. Response Surface Models

We use the $\bar{D}_{.i}$ described in equation (2) to build regression models of the response as a function of the aircraft system characteristics. Building separate models for each operational phase, casualty burden, and aircraft type (long range, short range) improves the quality and predictive accuracy of each model. Each model uses 96 data points that examine Mission Failure Rate, Speed, Capacity and Number of Aircraft at the levels defined in Table 3. A stepwise regression algorithm considers all main effects and interaction terms, as well as the squared terms for each of the four variables considered. We build two regression models for each combination of operational phase, casualty burden, and aircraft range. One model uses the set of \bar{D}_{1i} to capture the difference between a UAS and a single MV-22. The other model uses the set of \bar{D}_{2i} to capture the difference between a UAS and two MV-22s. Figure 6 illustrates the results from one model comparing UAS systems to one MV-22. Independent variable inputs are scaled to be on the interval [-1, 1].

Effect	Coefficient	t stat
CONSTANT	-10.07	-41.61
SPEED	-4.46	-37.11
SPEED*SPEED	3.34	15.72
NUM	-0.86	-7.63
CAP*CAP	1.21	5.74
NUM*SPEED	-0.79	-5.64
CAP	-0.55	-4.49
CAP*SPEED	-0.66	-4.35
NUM*NUM	0.50	2.72
NUM*CAP	0.28	2.01

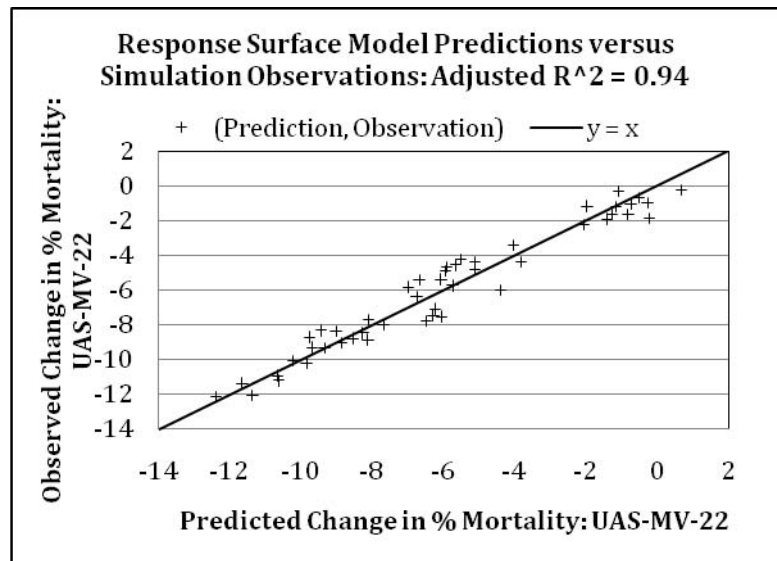


Figure 6. Regression for forward deployed long range UAS, Initial Assault, Moderate Casualty Burden

It is difficult to make any broad conclusions about desirable characteristics of a CASEVAC UAS because there are significant trade off's between attributes. For instance, having two aircraft available reduces the impact of aircraft speed and capacity. Generally we make the following observations about estimated patient mortality with respect to aircraft characteristics.

- Increasing capacity from one to two significantly improves patient movement times and estimated mortality, but increasing the capacity from two up to six produces little change. Data collected from 2004 to 2006 by Fulton et al indicate that fewer than 7% of CASEVAC missions moved more than 2 casualties at a time in Iraq [15]. Despite that data, we were surprised capacity wasn't more influential during the Initial Assault with heavy casualty burdens.
- Aircraft speed is a major factor influencing performance, but the marginal benefits rapidly decrease above about 300 kph. With two or three aircraft, UAS performance matches a single MV-22 with speeds between 220 kph and 350 kph (MV-22 at 440 kph)
- Increasing the number of UAS from one to two significantly improves performance; increasing the number of UAS from two to three significantly improves performance in most cases, but the change is smaller.
- When forward surgery is available, aircraft speed is much less important and aircraft range is not important so long as there are sufficient lifts of opportunity to move patients from the forward capabilities to the sea base.

We build 20 regression models to describe the response surface of this experiment and compile those models in a Microsoft Excel spreadsheet. The spreadsheet contains Visual Basic controls an analyst uses to select casualty burden, operational phase, and manipulate all other variables. As the controls are manipulated, the appropriate regression models plot the response of each aircraft type (short range, long range, forward deployed long range) in relation to the MV-22 baseline. Encapsulating the results of regression modeling this way provides a simple visual means of accessing a large amount of data, and makes analysis easier as well.

8. A Model for Degrading Patient Status During Evacuation

Assumption 8 in section 2 means the only penalty a patient incurs from relying on a LOO is any additional wait time; there is no estimate for the effect of the absence of a care provider. Featherstone similarly assumes that patient status doesn't degrade while on board a UAS without care providing capability [8]. These assumptions are weak parts of both analyses, and Figure 7 illustrates one potential reason why. As capacity of the dedicated aircraft increases, the number of Lift of Opportunity aircraft required to support patient movement decreases.

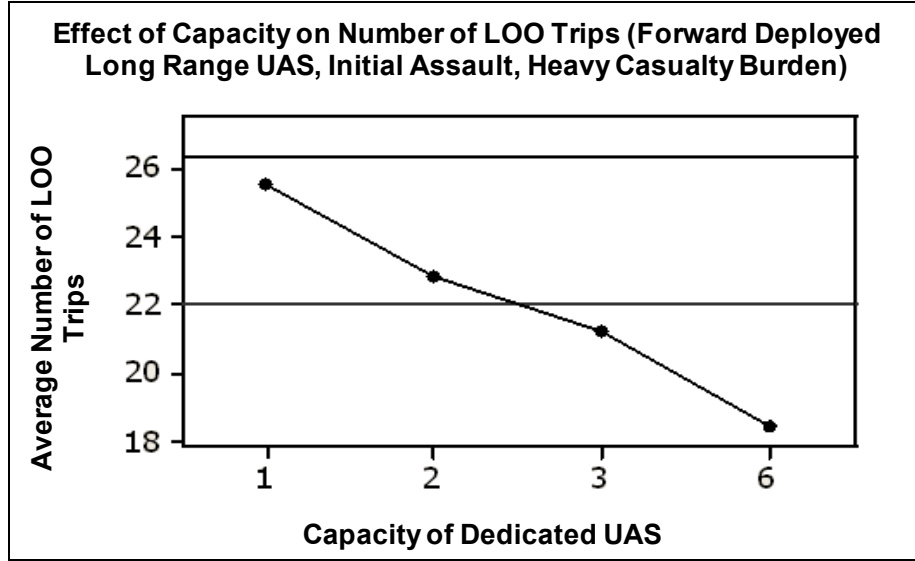


Figure 7 Effect of capacity on number of LOO trips

We were surprised that capacity did not have a larger influence on patient outcomes, particularly during the Initial Assault with a heavy casualty burden. If assumption 8 is incorrect, and the absence of a care provider significantly affects patient outcomes, our results with respect to capacity could drastically change. Anticipating future efforts to quantify how the level of care providing capability on transport affects patient outcomes, we present a model for measuring how patient degradation due to lack of en route care impacts mortality. TML+ uses the Weibull distribution to generate patient survival times. T is a random variable representing a patient's survival time with a given level of care. If T is distributed Weibull(a, b) where a is the scale parameter and b is the shape parameter, then T has the probability density function:

$$f(t) = \left(\frac{b}{a}\right) \left(\frac{t}{a}\right)^{(b-1)} e^{-\left(\frac{t}{a}\right)^b}, \quad t > 0 \quad (3)$$

cumulative density function:

$$P(T < t) = F(t) = \int_0^t \left(\frac{b}{a}\right) \left(\frac{y}{a}\right)^{(b-1)} e^{-\left(\frac{y}{a}\right)^b} dy = 1 - e^{-\left(\frac{t}{a}\right)^b}, \quad t > 0 \quad (4)$$

and survival function:

$$P(T > t) = S(t) = 1 - F(t) = e^{-\left(\frac{t}{a}\right)^b}, \quad t > 0 \quad (5)$$

The survival function gives the probability that a patient survives longer than some time t without receiving more advanced care. Because this survival time includes a patient's treatment and evacuation as described in section 0, we consider degrading a conditional survival function that applies only to the time a surviving patient spends on a transport. Figure 8 illustrates the idea. The survival functions in the graph are for a high risk patient at the first responder, but the same concept applies to any medical treatment facility, or from the point of

injury to the first responder. Zero on the x-axis is the time the patient begins treatment at a facility (or is wounded) and the survival curves give the probability that a patient is still alive at a given time on the x-axis.

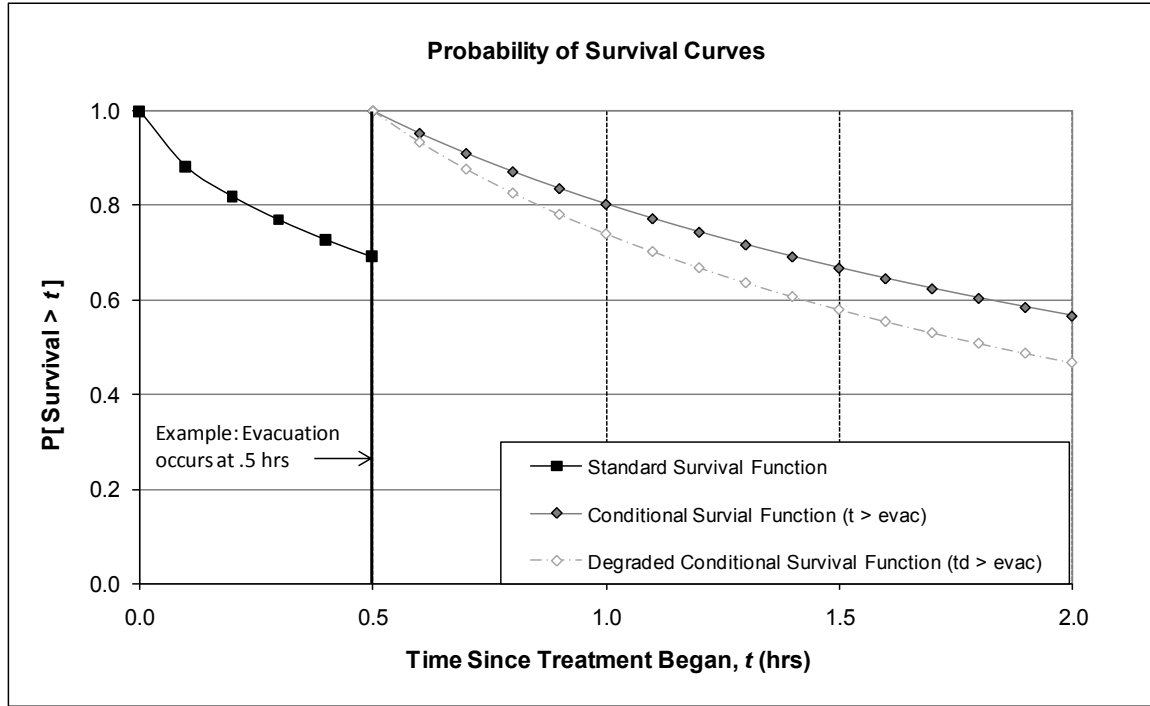


Figure 8 Conditional survival functions for degrading patient status during evacuation

At time t_E a surviving patient boards a transport for evacuation, 0.5 hours in the example above. First we develop the conditional survival function that gives the probability that a casualty survives longer than some time t given that they have already survived up to t_E . The conditional density function for t is defined in equation (6)

$$f^c(t) = \frac{f(t)}{S(t_E)}, t > t_E \quad (6)$$

Equation (7) gives the conditional survival function.

$$S^c(t) = P(T > t | t > t_E) = \int_t^\infty \frac{f(y)}{S(t_E)} dy = \frac{e^{\left(\frac{t_E}{a}\right)^b}}{e^{\left(\frac{t}{a}\right)^b}}, t > t_E \quad (7)$$

For convenience we introduce a translated random variable in equation (8)

$$t' = t - t_E, t' > 0 \quad (8)$$

and observe the translated conditional survival function in equation (9)

$$S^c(t') = \frac{e^{\left(\frac{t_E}{a}\right)^b}}{e^{\left(\frac{t' + t_E}{a}\right)^b}}, t' > 0 \quad (9)$$

Degrading the conditional survival function given in (9) is somewhat subjective. There are certainly many ways to define the ‘degraded’ function, but we propose that it simply means a patient’s survival time during evacuation on a transport without care providing capability is reduced by some factor. We consider t_d as a random variable representing a patient’s degraded survival time resulting from evacuation without care providing capability, and define it by the transformation $u(t')$ in equation (10); $w(t_d)$ is the inverse transformation function.

$$t_d = u(t') = kt' \Rightarrow t' = w(t_d) = \frac{t_d}{k}, \quad k \in [0,1] \quad (10)$$

The transformed random variable t_d reduces a patient’s survival time during transport by $100*(1-k)\%$. The true value of k is unknown, and the simple transformation above may not adequately describe the effects of traveling without en route care, but we propose it as an interim method for incorporating degraded care providing capability into a model. We derive the probability density function $g(t_d)$ of the conditional degraded random variable by evaluating the conditional density function of the transformed random variable in equation (11) as described by Hogg and Craig [16].

$$\begin{aligned} g(t_d) &= f^c(w(t_d)) \cdot \frac{d}{dt_d} [w(t_d)] = \left[e^{\left(\frac{t_E}{a}\right)^b} \left(\frac{b}{a}\right) \left(\frac{\frac{t_d}{k} + t_E}{a}\right)^{(b-1)} e^{-\left(\frac{\frac{t_d}{k} + t_E}{a}\right)^b} \right] \cdot \frac{1}{k} \\ &= e^{\left(\frac{t_E}{a}\right)^b} \left(\frac{b}{ak}\right) \left(\frac{t_d + kt_E}{ak}\right)^{(b-1)} e^{-\left(\frac{t_d + kt_E}{ak}\right)^b}, t_d > 0 \end{aligned} \quad (11)$$

The degraded conditional survival function $S_d^c(t_d)$ in equation (12) results from the same procedure in equation (7).

$$S_d^c(t_d) = \int_{t_d}^{\infty} g(y) dy = \frac{e^{\left(\frac{t_E}{a}\right)^b}}{e^{\left(\frac{t_d + kt_E}{ak}\right)^b}}, t_d > 0 \quad (12)$$

Even if the true value of k cannot be accurately estimated, or if the mechanism of degradation is much more complicated, these computations at least provide some sensitivity analysis capability to serve as a starting point for addressing the impact of en route care.

9. Conclusions and Recommendations

Fielding new autonomous aircraft specifically dedicated to MEDEVAC presents the military medical community with the unique opportunity to directly optimize the aircraft for that mission. While this analysis along with [8] provide some basic guidelines regarding how aircraft system characteristics influence performance, the acquisition of an aircraft system requires more thorough investigation. If the system will be supported by lifts of opportunity, those aircraft and all their aviation functions will influence the requirements of a dedicated MEDEVAC aircraft system. Considerations such as maintenance cycles and required down time, costs, aircraft footprint and weight should influence the acquisition process. More research on how en route care providing capability influences patient outcomes is necessary for a complete analysis. The current model of Navy Marine Corps casualty evacuation outside the joint environment is perhaps one dedicated aircraft supported by lifts of opportunity. Our analysis estimates patient mortality and demonstrates many systems that reduce the likelihood of death during evacuation by 10% compared to using one dedicated MV-22 for casualty evacuation. Other potential benefits from improving the evacuation system included reduced patient morbidity and reduced total time and cost of care.

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